This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



# Classification of Movement Preparation between Attended and Distracted Self-Paced Motor Tasks

S. Aliakbaryhosseinabadi, E. N. Kamavuako, *Member, IEEE*, N. Jiang, *Member, IEEE*, D. Farina, *Senior Member, IEEE* and N. Mrachacz-Kersting*

*Abstract*— ***Objective:*** **Brain-computer interface (BCI) systems aim to control external devices by using brain signals. The performance of these systems is influenced by the user's mental state, such as attention. In this study, we classified two attention states to a target task (attended and distracted task level) while attention to the task is altered by one of three types of distractors.** ***Methods:*** **Twenty-seven participants were allocated into three experimental groups and exposed to one type of distractor. An attended condition that was the same across the three groups comprised only the main task execution (self-paced dorsi-flexion) while the distracted condition was concurrent execution of the main task and an oddball task (dual-task condition). EEG signals were recorded from 28 electrodes to classify the two attention states of attended or distracted task conditions by extracting temporal and spectral features.** ***Results:*** **The results showed that the ensemble classification accuracy using the combination of temporal and spectral features (spectro-temporal features, 82.3±2.7%) was greater than using temporal (69±2.2%) and spectral (80.3±2.6%) features separately. The classification accuracy was computed using a combination of different channel locations and it was demonstrated that a combination of parietal and centrally located channels was superior for classification of two attention states during movement preparation (parietal channels: 84.6±1.3 %, central and parietal channels: 87.2±1.5 %).** ***Conclusion:*** **It is possible to monitor the users' attention to the task for different types of distractors.** ***Significance:*** **It has implications for online BCI systems where the requirement is for high accuracy of intention detection.**

*Index Terms*— **Attention diversion, Classification of movement preparation, Brain-computer interface (BCI), Channel selection, Dual tasking.**

## I. Introduction

BRAIN-COMPUTER INTERFACE (BCI) systems designed for neurorehabilitation allow a bidirectional interaction between the user and the external environment by translating brain signals into external commands [1, 2]. For the past 10 years, we have developed a BCI system designed for neuromodulation in which precise time of movement onset detection is imperative for plasticity induction [3], [4, 5]. In these past studies, we have relied almost exclusively on the detection of the movement related cortical potential (MRCP) as our control signal modality. However, to detect movement onset, previous studies have implemented several other methods which may lead to an improved detection accuracy and latency from electroencephalography (EEG) signals. For example, by monitoring variations in the power spectral density of EEG signals, it has been possible to detect mental task transitions from idle to imagination of self-paced movements with an accuracy of ~70% [6]. Alternatively, detection of movement onset could be identified by analyzing the temporal structure of EEG signals in relation to movement preparation [7]. Nevertheless, none of these previous studies have included the influencing factors of the user's mental state in the experimental paradigms, such as fatigue [8], attention [9] and emotion [10].

Attention is defined as the ability to focus on the relevant tasks/stimuli. In real-life situations, there are various types of distractors that drift attention from a specific task, such as visual, auditory and a combination of these [11-13]. Each type of attention change will activate corresponding parts of the brain. For example, auditory distractors will activate neurons located within the temporal and frontal lobes [14, 15] while visual stimulus processing will activate neurons within the occipital and parietal lobes [16, 17]. Furthermore, there are three separable brain networks that each perform three attention functions; alerting, orienting and executive control [18]. Alerting may be considered one component of arousal and serves to ensure the readiness to respond to an external stimulus. This network involves primarily frontal and parietal brain regions [19]. Orienting is the ability of prioritizing sensory information through the selection of modality and location. The network is confined mainly to the frontal lobe and the superior and inferior parietal lobe [20, 21]. Executive control may also be referred to as focal attention and represents the moment of target detection where the subject becomes consciously aware of the target. This network is widespread and

* Research was supported by the Obel Foundation

S. Alikabaryhooseinabadi and N. Mrachacz-Kersting are with the Center for Sensory-Motor Interaction, Department of Health Science and Technology, Aalborg University, DK-9220 Aalborg, Denmark (email: sal@hst.aau.dk; enk@hst.aau.dk; correspondence* nm@hst.aau.dk).

E.N. Kamavuako is with the Centre for Robotics Research, Department of Informatics, King's College London, London WC2B 4BG, United Kingdom (email: ernest.kamavuako@kcl.ac.uk)

N. Jiang is with the System Design Engineering Department, Center for Bioengineering and Biotechnology, University of Waterloo, Canada (email: ning.jiang@uwaterloo.ca )

D. Farina is with Department of Bioengineering, Imperial College London, SW7 2AZ London, UK (email: d.farina@imperial.ac.uk )

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



involves neurons within the anterior cingulate cortex, medial frontal cortex and the lateral prefrontal cortex [22].

In our MRCP based BCI (3, 4, 5), the central electrode is located over Cz (when targeting lower limb movements) and the remaining channels over frontal and parietal brain regions. Since these areas correspond to those of the attention networks, interference from the firing of their neurons with firing of neurons involved in motor planning and execution will lead to reduced detection accuracies. In our previous studies [23-25], we demonstrated that changes in attention significantly deteriorate MRCP detection in synchronous BCIs, using auditory distractors. Further, classification of different states of attention attains accuracies of 68% but only for EEG channels located over the motor cortex [25]. This may be further enhanced to 73% by using a combination of time-frequency features [25].

In the current study, we expanded on our previous results by quantifying variations in motor movement preparation with and without distractors in self-paced motor executions. The distractor was comprised of three different types, auditory, visual or a combination of these. Three types of EEG features, temporal, spectral and spectro-temporal (using temporal and spectral features concurrently) were used to classify the preparation phase between the focused (without distractor) and distracted attention state (with distractor). We hypothesized that EEG signal patterns measured during a dorsiflexion task under attended conditions are different from distracted conditions in both the time and frequency domain. Based on our previous studies using cue-based movements we hypothesize that tempo-spectral features will result in the highest classification accuracy compared to temporal or spectral features alone. Moreover, we hypothesize that it is possible to identify the brain regions most significantly influenced by visual, auditory and a combination of these distractors. Proof of this latter hypothesis is important for the design of a clinical BCI as it will provide information on the minimum number of EEG channels necessary for classifying the attention state to the movement in real-time self-paced BCI systems.

## II. Methods

### A. Participants

Twenty-seven participants (thirteen females, fourteen males) divided into three groups of nine participants (mean age 26.1± 4.2; 27.1±1.6; 28.2±4.4) took part. None of the participants had any hearing or visual abnormality and all were free from neurological disease. All procedures were approved by the local ethical committee for the region of Northern Jutland (N-2016006).

### B. Experimental Setup

EEG signals were recorded from twenty-eight mono-polar electrodes using an active EEG electrode system (g. GAMMAcap$^2$, Austria) and g.USBamp amplifier (gTec, GmbH, Austria). Signals were recorded from AF3, AFz, Af4, F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2 and P4 located based on the standard international 10-20 system. The reference electrode was attached to the right earlobe and the ground electrode was placed on FP1. Bipolar surface electromyography (EMG) signals were positioned on the tibialis anterior (TA) muscle of the dominant foot. All signals were sampled at a frequency of 256 Hz with 16 bits accuracy.

### C. Paradigms and Tasks

Each participant was asked to sit in a comfortable chair approximately one meter away from a digital screen while their feet were resting on a step with the knee joint at approximately 90°. The visual oddball was displayed at the center of the screen while the auditory oddball was played via a conventional headphone binaurally. The experiment contained two attention states, an attended level where participants had to perform self-paced ankle dorsiflexion movements alone, and diverted attention where participants had to perform the self-paced motor task while their attention was diverted using either the visual oddball, the auditory oddball or a combination of these two (as outlined below). The visual or auditory oddball contained various visual or auditory stimuli with one specified as the target that the participants had to identify. This target was not as frequent as the other (standard) stimuli, requiring more attention to be detected [26, 27]. Each oddball is described in more detail in the sections below. The dominant foot was selected based on the Edinburgh Handedness Inventory.

Each group of participants completed a total 120 trials of self-paced ankle dorsiflexion divided into four blocks. Two blocks consisted in performing the motor task only, while the remaining two blocks involved exposure to either the visual oddball (n=9), the auditory oddball (n=9), or a combination of the two (n=9). Blocks with either the motor task alone or in combination with a distractor (described in detail below and illustrated in Fig. 1a and 1b), were counterbalanced to minimize the influence of task learning.

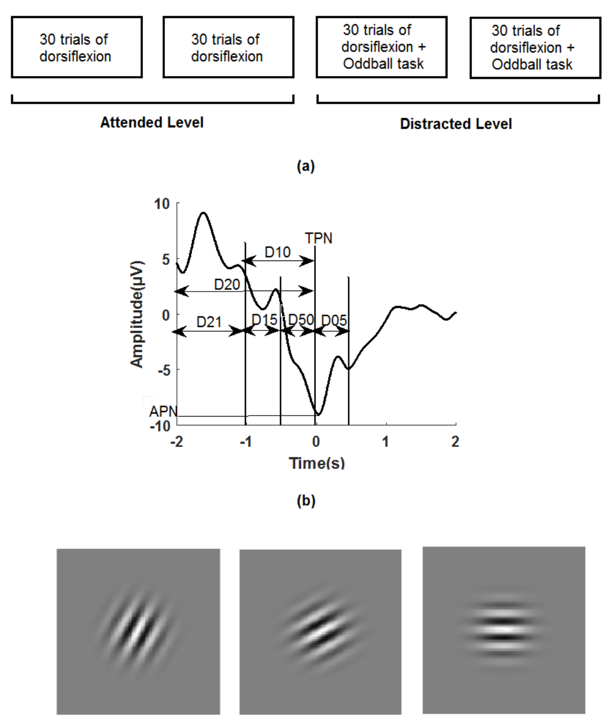



Fig. 1. **(a)** Illustration of experimental blocks in attended and distracted level. Attended level contained two blocks with 30 trials of ankle dorsiflexion while the distracted level had two blocks of dual-tasking of dorsiflexion in addition to the oddball task. **(b)** Six time slots were used for feature extraction with regards to the movement onset obtained from EMG analysis. The time and place of peak negativity are also shown. **(c)** Three types of visual distractor that are Gabor masks with an orientation of 30°, 60° and 90° from left to right.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



<u>Attended Level (AL)</u>: This contained two blocks of self-paced ankle dorsiflexion movements. Participants were asked to focus on the movement of ankle dorsiflexion and execute it as rapidly and forcefully as possible and to hold it for at least two seconds. Furthermore, participants were instructed to allow a few seconds of rest between two trials in order to avoid repetitive movements and fatigue. Blocks were interspersed with a three minute rest period.

<u>Distracted Attention Level (DAL)</u>: In addition to performing ankle dorsiflexion as outlined above, one of three types of oddballs were played depending on the experimental group. Participants were instructed to count the number of target sequences (dual-tasking). Oddballs played randomly and dorsiflexion was self-paced.

In the diverted attention state, participants were challenged with one of the three types of oddball stimuli considered as attention distractors as outlined in the following.

<u>Visual distracted attention level (VDAL)</u>: The visual oddball included three Gabor masks with various orientations (Fig. 1c). The Gabor mask is a Gaussian kernel function modulated with sinusoidal waves. The most frequent Gabor with an orientation of 90º and a probability of 50% appeared on the screen while two other Gabor had an orientation of 30º and 60º and were each displayed with a probability of 25%. All visual stimuli had a duration of 200 ms and a randomized inter-stimulus interval (ISI) of 1-2 s. On average 280 visual stimuli were shown on the screen while participants had to count the number of one of the target sequences in each block. The target sequence was either Gabor 60º that appeared immediately after Gabor 90º or Gabor 30º that appeared immediately after Gabor 90º.

<u>Auditory distracted attention level (ADAL)</u>: The Auditory oddball contained three tones. The 'low' pitch tone had a frequency of 500 Hz and was the most probable tone with a probability of 50%. The 'middle' and 'high' pitch tones had frequency of 1200 Hz and 1900 Hz respectively, and each played with a probability of 25%. The duration of each sound was 200 ms with a 10 ms fall/rise time and a sound pressure level of 75 dB. The ISI was randomized in a range of 1-2 s. On average 270 auditory tones were played while participants were asked to count the number of a target sequence. The target sequence could be the middle pitch immediately following the low pitch or the high pitch immediately following the low pitch.

<u>Audiovisual distracted attention level (AVDAL)</u>: This type of oddball was a combination of both visual and auditory oddballs, providing a bi-modal distractor. Two Gabor masks with an orientation of 60º and 30º and each with the probability of 25% were displayed on the center of the screen. Additionally, two auditory tones with frequencies of 1200 and 1900 Hz were played (middle and high pitch), each with a probability of 25%. All stimuli were randomized with an ISI of 1-2 s and a duration of 200 ms. On average 130 auditory tones and 140 visual stimuli were played while participants were asked to count the number of the target sequence. This target sequence was either the number of Gabor 30º following the middle pitch sound or the number of high pitch sounds following the Gabor 60º.

### D. Movement Performance

The correlation among EMG envelopes in each block was computed to quantify the consistency of movement execution across trials (dorsiflexion). EMG envelopes were computed by rectification and low pass filtering (Butterworth filter) with a cut off frequency of 10 Hz. The average correlation of EMG envelopes was computed among all trials in each block. Moreover, power of EMG trials were computed in the range of [-.2 2] s with respect to movement onset.

The performance of target detection was defined as the number of errors in counting. Based on this, the difference between the real number of target sequences and the number of counted sequences by the subjects was computed to show the performance of the oddball task.

### E. P300 Analysis

ERP components were analyzed from the outputs of channel Cz as it was shown that this channel can differentiate between attended and distracted task by generating larger P300 amplitude [28]. The EEG signals were band-pass filtered in the range of [1 10] Hz and ERP trials extracted in the time window of [-0.1 1] sec with regards to the onset of the distractor stimulus. Trials with eye blinks and muscle artifacts were removed. The P300 was defined as the largest amplitude in range of [-100 700] ms with respect to the onset of stimuli. The P300 component was extracted for three types of distractors and compared between attended and distracted levels to represent attention variations during movement preparation.

### F. Feature Extraction

MRCP features were used for time domain analysis. EEG signals were filtered in the range 0.05-10 Hz using a second order band-pass Butterworth filter. MRCP trials were extracted in the range of [-2 2] s with respect to movement onset obtained from EMG signals. Trials contaminated by the electrooculogram (EOG) were detected using a threshold of 120 μV and removed.

Twenty temporal features were extracted from single trials of MRCP. The amplitude of the peak negativity and the time of peak negativity (APN and TPN) were extracted from each trial. Six slopes obtained from linear regression in the six time intervals [-2 0] s, [-2 -1] s, [-1 0] s, [-1 -.5] s, [-.5 0] s, and [0 1] s were computed (0 indicates the movement onset obtained from EMG analysis). Additionally, six variability of each trial defined as the standard deviation and the six mean value of the MRCP amplitude were also computed in the same six time domains of the slope computation. From each of the six time slots, one slope, one variability and one mean amplitude were extracted.

Twenty spectral features were extracted from the power spectral density in five frequency bands and four time intervals. The frequency bands were the Delta ([0 3] Hz), Theta ([4 8] Hz), Alpha ([8 13] Hz), Beta ([13 31] Hz), and Gamma ([31 100] Hz), and time intervals were [-2 0] s, [-2 -1] s, [-1 0] s, and [0 1] s. The power of the signal in each frequency band was computed in four time intervals.

In addition, a combination of these two groups of features was also used to obtain a spectro-temporal feature space of dimension 40.

### G. Classification Procedure

#### 1) Classification of attention state with attention diversion

Initially we selected the best subset of features among temporal, spectral and spectro-temporal features for classification of movement preparation with and without distractor. The classification was performed using each group of features for each participant within different distractors (Fig. 2). The dimension of the feature space was

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



reduced using principal component analysis (PCA) by selecting six temporal and six spectral features.

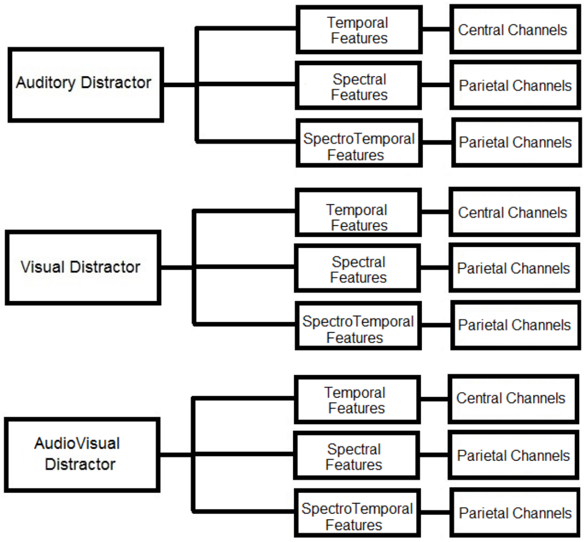



Fig. 2. Diagram of steps for classification of movement preparation. Three types of features were extracted from raw data of each distractor for each single participant. Classification accuracy was compared based on brain locations and brain hemisphere to find the best channel location for classification of movement preparation. The selected locations corresponding for each feature type shown in the last column of the diagram.

A linear discriminant analysis (LDA) classifier was tested with a 10-fold cross-validation procedure [for details see [29]. The trials were divided in ten sets of which 9 were used for training and one for testing.

The results of classification within each group of features was compared among six brain locations that were labeled as Anterio-frontal (AF3, AFz, AF4), Frontal (F3, F1, Fz, F2, F4), Fronto-central (FC3, FC1, FCz, FC2, FC4), Central (C3, C1, Cz, C2, C4), Centro-parietal (CP3, CP1, CPz, CP2, CP4) and Parietal (P3, P1, Pz, P2, P4). Furthermore, the classification output was compared among the right hemisphere, the left hemisphere and the channels located over the midline. The right hemisphere corresponded to the channels AF4, F2, F4, FC2, FC4, C2, C4, CP2, CP4, P2 and P4, the channels located over the midline to AFz, Fz, FCz, Cz, CPz and Pz, and the left hemisphere to AF3, F1, F3, FC1, FC3, C1, C3, CP1, CP3, P1 and P3.

#### 2) *Channel selection*

From the initial results obtained as outlined above (section 2.6.1), the best channel location(s) and best channel hemisphere(s) were chosen based on the classification accuracy. As different channel locations were selected for two groups of temporal and spectral features, it may be possible to increase classification accuracy by combining more channels from different lobes or hemispheres to the selected brain parts. We thus performed a sequential forward selection (SFS) based on EEG channels [30]. The SFS method in the current study started from the channel location with the highest accuracy (initial seed) and then more channels were added to this initial seed if classification accuracy was improved.

### *H. Statistics*

Wilcoxon matched-pair sign rank test was applied to measure the differences of EMG envelops and EMG power. The number of errors in oddball tasks was compared by using the same method. Our statistical analysis does allow us to compare between distractor types even if the participants were not taking part in all three distractors. The results of each group of features were compared between distractors by using paired t-test. Two-way analysis of variance (ANOVA) was used to compare classification accuracy in each group of features (temporal, spectral and spectro-temporal). Two main factors were: 'channel hemisphere' with three levels of: channels located in the left hemisphere, channels placed on the right hemisphere and channels located over the midline and 'channel location' with six levels of: anterio-frontal, frontal, fronto-central, central, centro-parietal and parietal. In addition, the accuracy obtained from three groups of features was compared using paired t-tests to establish the appropriate feature type for classification of movement preparation with and without distractor. Normality of data was tested with Kolmogorov-Smirnov method ($p<0.05$).

## III. Results

As illustrated in Fig. 3 among different feature types, spectro-temporal features showed superior classification accuracy (~85%) than temporal (~70%) and spectral features (~79%) in all types of attention distractors. By using spectral and spectro-temporal features, channels located over the parietal lobe (~84%) are superior in detection attentional shifts as compared to the other channel locations.

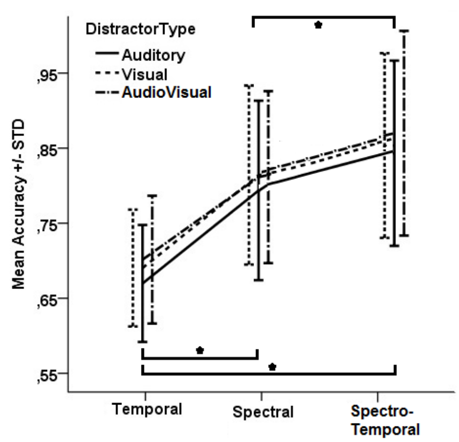



Fig. 3. Comparison of different feature types for classification of movement preparation with various types of distractors. It is implied that spectro-temporal features had the best classification results in comparing with temporal and spectral features.

### *A. Movement Performance*

Fig. 4a shows the mean value of the TA EMG envelops across all participants for both the simple motor task (AL) and for DAL with distractors. There was no significant difference between any of the conditions tested ($p>0.05$), indicating that the performance of the motor task did not depend on the attention state. The power of EMG trials was decreased in the distracted level in comparison to the attended level (Fig. 4b) attaining average values of 3.4, 3.5 and 3.5 $\mu V^2$ for the ADAL, VDAL and MDAL respectively as compared to 3.6, 3.5 and 3.6

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



$\mu V^2$for the AL. However, this difference did not reach statistical significance ($p>0.05$). The average number of errors in target detection was 5.6±4.7 for VDAL, 6.9±5.3 for ADAL and 5.9±3.1 for AVDAL. There was no significant difference in oddball performance among the different types of distractors ($p>0.05$).

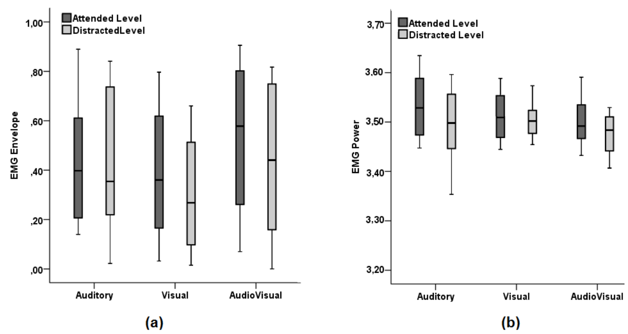



Fig. 4. **(a)** Comparison of the mean EMG envelope during movement execution for the control level and the diverted attention states using either the auditory oddball, the visual oddball or a mix of these as the distractor. Each bar represents the average of nine participants. **(b)** Comparison of differences in EMG power for the attended level and the distracted levels of ADAL, VDAL and AVDAL using the auditory oddball, the visual oddball or a mix of these as the distractor. Each bar represents the average of nine participants.

Fig. 5a illustrates an example of the MRCP from one participant for all channel locations while performing the dorsiflexion task alone (AL) or with an audiovisual distractor (AVDAL). For this participant, the amplitude and slopes of the MRCP were reduced in all channels when performing the dual task as opposed to the single motor task, particularly during movement preparation (prior to movement onset). In channel Cz, the amplitude of the peak negativity decreased from -12.3 μV in the attended level to -4.3μV in the distracted level. It was similar for pre-phase slopes in the range of [-2 0] s by reducing from -6.2 μV/s to -1.6 μV/s. Fig. 5b displays the power distribution obtained from the short-time Fourier transform in the same participant for the time course of [-0.6 -0.4]s corresponding to either the movement onset. The Theta and Alpha frequency bands showed more changes from single to dual-task conditions in comparison to the Beta and Gamma bands. According to the movement onset, the power of Alpha increased while in the case of the oddball onset, that was decreased. The majority of Alpha band variations were localized in the central and frontal channel locations although for the oddball stimuli they were located in the parietal and centro-parietal channels.

## B. *P300 results*

The results of the one-way ANOVA demonstrated that the amplitude of the P300 was significantly increased from attended to the distracted level for the auditory distractor ($F_{(1,14)}=5.1$, $p=0.04$), the visual distractor ($F_{(1,14)}=4.9$, $p=0.04$) and the audiovisual distractor ($F_{(5,206)}=5.3$, $p=0.04$). The grand average of the P300 amplitude across all participants is illustrated in Fig. 6. For the auditory distractor the amplitude increased from 4.8±1.5 in the attended level to 5.8±1.9 μV in the distracted level. The amplitude was increased from 3.1±0.4 to 3.8±0.8 μV by using the visual distractor. In the condition of the audiovisual distractor, the amplitude in the attended level increased from 2.9±0.8 to 3.6±1 μV in the distracted level.

## C. *Classification*

### 1) *Comparison of distractors*

The results of the paired t-test comparison confirmed that there was no significant difference among distractor types ($p>0.05$).

### 2) *Auditory distracted attention level (ADAL)*

Two-way ANOVA revealed that only the factor channel location had a significant effect on classification accuracy from temporal features when the auditory oddball acted as the distractor ($F_{(5,206)}=2.5$, $p=0.03$; 65.9 to 71.9%). *Post-hoc* tests revealed that classification accuracy was significantly better for the central locations compared to the parietal ($p=0.01$) and centro-parietal locations ($p=0.04$). Similarly, classification accuracy according to spectral features was significantly different depending on channel location ($F_{(5,206)}=2.5$, $p=0.04$; 74.5 to 79.8%). The accuracy for channels located in the parietal location was significantly higher compared to frontal channels (Bonferroni *Post-hoc test* $p=0.04$). Spectro-temporal accuracies were also significantly different with regards to the channel location ($F_{(5,206)}=2.6$, $p=0.03$; 70.6 to 84.5%). *Post-hoc tests* showed that classification accuracy was significantly different for parietal channels compared to those in the anterio-frontal region ($p=0.04$). Table. 1 and Table. 2 present the classification accuracy for channels in various brain locations and brain hemispheres for the auditory oddball task as compared to the motor task.

Spectral and spectro-temporal features performed significantly better than time domain features (spectral features: $t_{(223)}=-10.8$, $p<0.001$; spectro-temporal: $t_{(223)}=-16$, $p<0.001$). In addition, spectro-temporal features had a significantly higher classification accuracy compared to spectral features ($t_{(223)}=-3.5$, $p<0.001$) (Fig. 3).

### 3) *Visual distracted attention level (VDAL)*

Channel location was the only factor that had a significant effect on the classification accuracy from the temporal features when the visual oddball played the role of distractor (temporal: $F_{(5,206)}=2.6$, $p=0.03$; 66.4 to 72.8%). *Post-hoc* test revealed that classification accuracy was significantly better for central channel locations compared to the centro-parietal channels ($p=0.02$) and anterio-frontal lobe ($p=0.02$). Classification accuracy based on the spectral features was significantly different among the six channel locations ($F_{(5,206)}=2.3$, $p=0.04$; 70.1 to 79.3%). According to the *Post-hoc test,* the accuracy for channels over the parietal location was significantly higher in comparison to those in the anterio-frontal region ($p=0.03$). Spectro-temporal accuracies were significantly different regarding to channel locations ($F_{(5,206)}=2.4$, $p=0.03$; 73.3 to 84.6%). There was a significant difference between parietal and anterio-frontal channel locations ($p=0.04$).

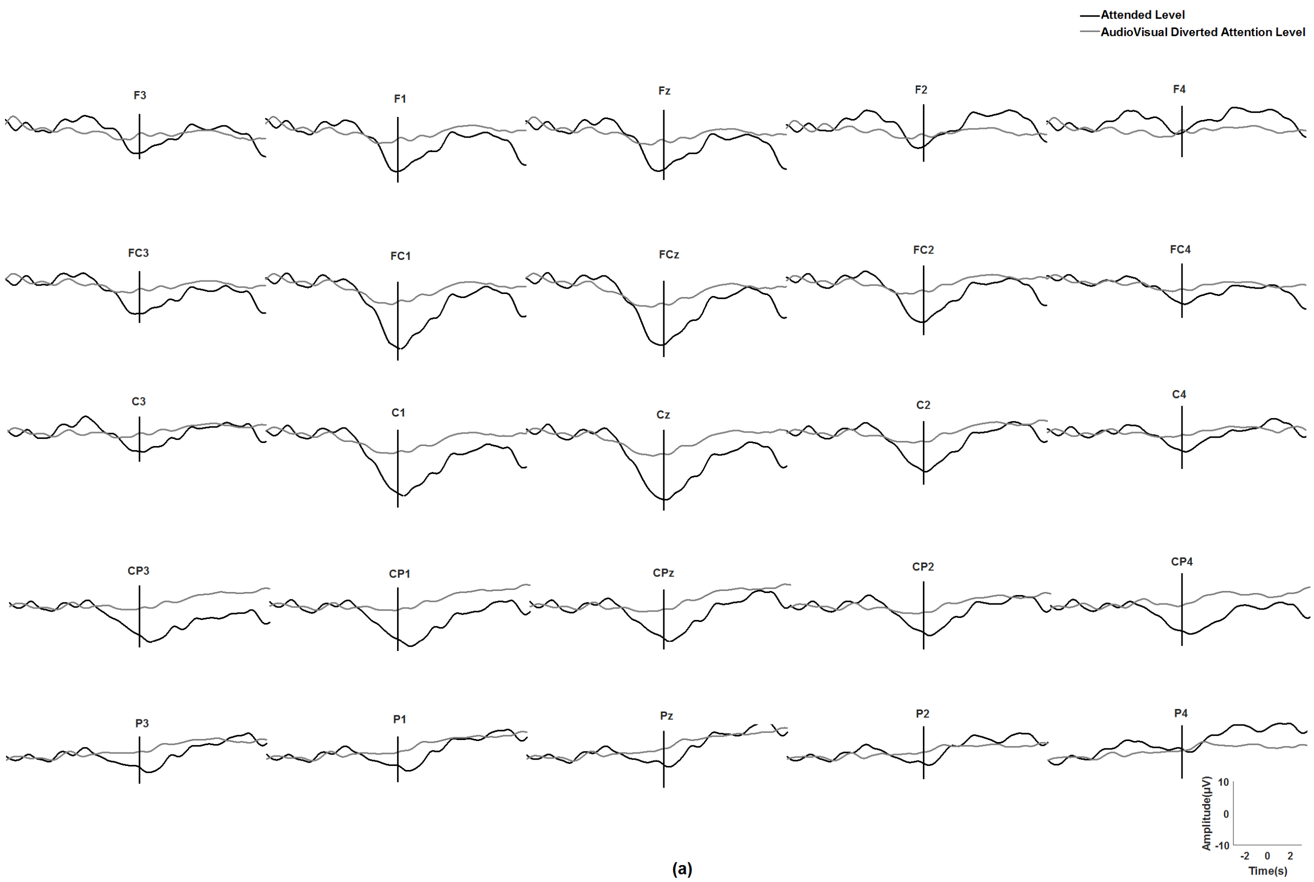
Classification accuracy with spectral and spectro-temporal features were significantly higher in comparison with temporal features (spectral: $t_{(223)}=-13.5$, $p<0.001$; spectro-temporal: $t_{(223)}=-15$, $p<0.001$ ). Also, spectro-temporal features represented significantly higher classification accuracies compared to spectral features ($t_{(223)}=-3.2$, $p=0.002$).

### 4) *Audiovisual distracted attention level (AVDAL)*

Classification accuracy from temporal features was significantly affected by channel location ($F_{(5,206)}=2.7$, $p=0.02$; 65.4 to 73.2%). *Post- hoc tests* showed that the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering





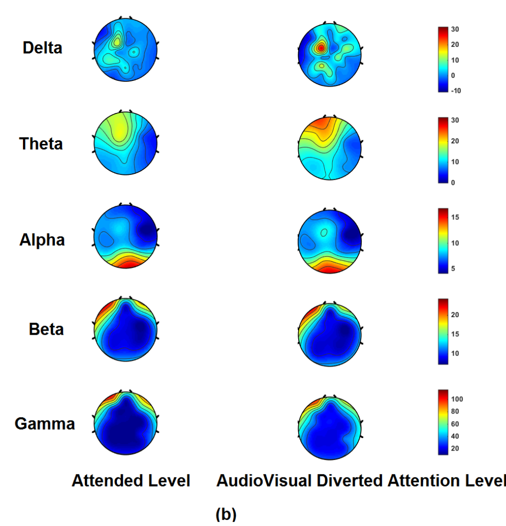




Fig. 5. **(a)** A sample of MRCP signals in different channel locations for the attended level (black curves) and AVDAL (gray curves) from a single participant. Black lines on each MRCP curve shows time zero point. **(b)** A sample of the topographic distribution of power density in five main frequency ranges from a single participant. The left column is the control level and the right column illustrates AVDAL.

accuracy of central channels was significantly better compared to the frontal ($p=0.02$) and anterio-frontal ($p=0.03$) channels. Spectral feature accuracy was significantly different among various channel locations ($F_{(5,206)}=2.4$, $p=0.04$; 71.2 to 83.4%). Channels located in the parietal region had a significantly higher accuracy than those of the frontal region ($p= 0.4$) and anterio-frontal area ($p=0.03$). Channel location also demonstrated a significant effect on accuracy from spectro-temporal features ($F_{(5,206)}=2.4$, $p=0.04$; 73.5 to 86.6%). Channels within the parietal region had a significantly higher accuracy than those in the frontal region ($p= 0.4$).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2019.2900206, IEEE Transactions on Biomedical Engineering



Student's t-test revealed significant differences between temporal and spectral features ($t_{(223)}$=-11.6, p<0.001) and also between temporal and spectro-temporal features ($t_{(223)}$=-14.8, p<0.001). Spectro-temporal features had a significantly higher accuracy than spectral features ($t_{(223)}$=-5.8, p<0.001). A summary of the differences among three groups of features (temporal, spectral and spectro-temporal) are illustrated in Fig. 3. Spectro-temporal and spectral features have a higher accuracy than temporal features alone for all types of the distractors while the combination of spectro-temporal is the best feature group attaining an accuracy of 84%.

TABLE I

CLASSIFICATION ACCURACY BASED ON DIFFERENT BRAIN LOCATIONS OF ANTERIO-FRONTAL, FRONTAL, FRONTO-CENTRAL, CENTRAL, CENTRO-PARIETAL AND PARIETAL LOBES. THE SIGNIFICANT DIFFERENCES ARE SHOWN IN GRAY

| | | Anterio-Frontal | Frontal | Fronto-central | Central | Centro-parietal | Pariet |
|---|---|---|---|---|---|---|---|
| Auditory | Temporal | 66.9±7.9 | 67.6±8.5 | 68.5±8 | 71.2±5.5 | 66.7±8 | 65.5± |
| | Spectral | 78.6±11.4 | 77.5±11 | 79.8±12.7 | 79.4±12.3 | 77.1±13.2 | 83.5± |
| | Spectro-temporal | 79.4±14.5 | 80.5±12 | 81.7±12.7 | 84.1±9.8 | 78.6±14.7 | 85.5± |
| Visual | Temporal | 66±4.7 | 68.9±7.1 | 69.4±8.8 | 72.8±5.5 | 66.4±8.5 | 70.4± |
| | Spectral | 77.8±9.5 | 81.7±7.1 | 80.6±14.4 | 81.1±14 | 80±13.5 | 85.1± |
| | Spectro-temporal | 78.6±10.9 | 80.7±9.6 | 84.9±12.1 | 83.6±13.8 | 80.2±15.3 | 83.7± |
| AudioVisual | Temporal | 67.4±12 | 68±10.6 | 71.8±5.3 | 73.2±6 | 68.6±8.2 | 69.6± |
| | Spectral | 78.6±8.9 | 78.7±10.7 | 81.3±10.9 | 81.8±11.4 | 77.5±15.3 | 86±8 |
| | Spectro-temporal | 82.9±10.1 | 81.3±14.8 | 82±14 | 86.2±12.7 | 80.1±17 | 88.1± |

## D. Channel Combination

The results presented above indicated that the central channels (C3, C1, Cz, C2 and C4) led to the highest classification accuracy for changes in attention when temporal features were extracted. Conversely, channels located in the parietal location (P3, P1, Pz, P2 and P4) were superior when using spectral and spectro-temporal features. The features of each group of these channels were subsequently considered as the initial point for the application of the SFS method.

Comparison of results demonstrated that although adding channels improved classification accuracy, it increased significantly by using spectro-temporal features from Cz, C2 and C4 in addition to the parietal channels. Accuracy increased significantly in both ADAL (t(7)= 2.5, P= 0.04; parietal channels: 85.5±9.4%, parietal and central channels: 88.2±12.3%) and VDAL (t(7)= 2.6, P= 0.03; parietal channels: 83.7±8.9%, parietal and central channels :86.1±15.2% ).

TABLE II

CLASSIFICATION ACCURACY BASED ON THREE HEMISPHERES OF CHANNEL PLACEMENTS. THERE WAS NOT ANY SIGNIFICANT DIFFERENCE BASED ON CHANNEL HEMISPHERE.

| | | | | |
|---|---|---|---|---|
| Auditory | Temporal | 67.4±7.7 | 67.9±7.4 | 66.3±8.2 |
| | Spectral | 80.5±11.1 | 79.7±11.6 | 78.7±13 |
| | Spectro-temporal | 83.1±12.3 | 81.7±12.9 | 81.1±12.2 |
| Visual | Temporal | 69.8±8.5 | 70.8±6.3 | 70.2±7.8 |
| | Spectral | 81.1±11.9 | 82.4±10.2 | 81.2±12.8 |
| | Spectro-temporal | 82.7±13 | 84±12.1 | 82.5±11.8 |
| Audiovisual | Temporal | 69.6±8.7 | 70±9.2 | 70.8±7.9 |
| | Spectral | 82.4±12.2 | 79.5±10.6 | 81.6±11.1 |
| | Spectro-temporal | 85.6±14.3 | 86.1±15.2 | 85.4±12.1 |

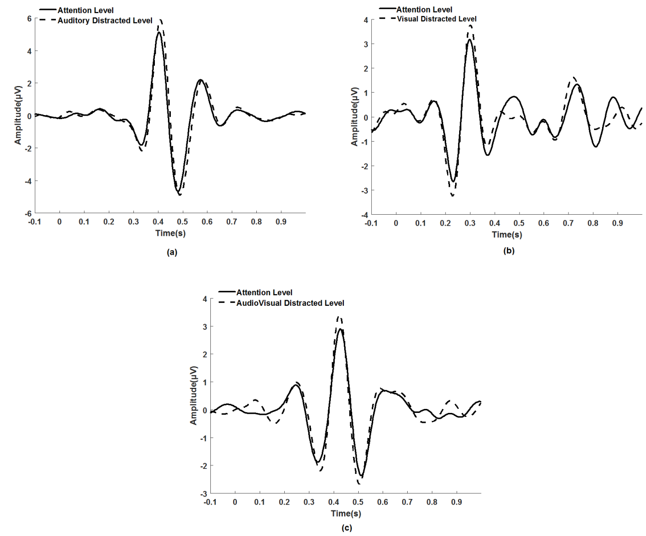



Fig. 6. Grand average of ERP signals across all participants from channel Cz for the attention level (solid lines) and three different types of distractors (dashed lines). Shown are the P300 components for (a) the auditory distractor (n=9) (b) the visual distractor (n=9) and (c) the audiovisual distractor (n=9).

## IV. Discussion

Three types of distractors with either a single modality (visual or auditory oddball) or bimodality (a combination of the visual and auditory oddball) were applied to divert the attention away from the main task (dorsiflexion). Testing all three levels is important since attention can be distracted in the real life scenario by visual or auditory means. Increments in P300 amplitude revealed that attention to the oddball stimuli was increased in the distracted attention state [31, 32] and thus attention was diverted from dorsiflexion to the oddball counting. In all types of distractors, movement detection from EEG was significantly influenced in the dual task condition likely due to a reduction in preparation time, since movement execution (as quantified by the EMG envelope and EMG power) was not affected. The results of oddball counting demonstrated that the number of errors were not significantly different among the three distractors and thus participants had the same oddball performance across the three conditions. Results from the EEG analysis suggest that when spectral or spectro-temporal features are extracted for classification purposes, channels located over the parietal location have the highest accuracy compared to other locations. The alpha power based on the oddball onset decreased in the dual-task conditions indicating that attention to sensory information in channels located in the parietal region was increased.

In the current study, the increment of alpha power based on the movement onset in central channel locations during the dual-task condition (Figure 5b) suggests that attention to the movement was reduced. This is in line with previous work that demonstrated a decrement of alpha power in the occipital lobe with increments in visual attention [33,34,35]. In that study two monkeys performed an intermodal selective attention task by responding to the visual or auditory stimuli. Theta power obtained from channels located in the frontal-midline region on the other hand, is a good indicator for task load which is higher in the case of higher task demand [36]. In the current study, theta power of the frontal lobe was increased in the dual-task conditions suggesting a higher task load (Figure 5b).

Attention discrimination attained values of approximately 84% by using spectro-temporal features as compared to 67% when extracting only temporal features from the same channels. However, when temporal features were extracted from channels located over the central location, classification accuracy was approximately 72%. A combination of spectro-temporal features from central and parietal channel locations significantly improved the classification accuracy to 87%. Although in BCI system design, it is desirable to reduce the number of channels for EEG recording, classification of movement preparation with and without a distractor is also vital for online BCI systems. The results presented show that a combination of channels placed on the central and parietal cortex and using spectro-temporal features is optimal for the classification of the attention state.

### *A. Classification of movement preparation with and without a distractor*

In previous studies, we have shown that temporal features of the MRCP can detect attention diversion in a cue-based BCI [23]. Specifically, the preparation phase was significantly altered when attention was diverted [23, 25] due to lower signal to noise ratio and less prominent features. Furthermore, additional components such as the P300 affected the MRCP signals and thus increased the differences between focused and diverted attention levels. When the MRCP is used as the control signal for a BCI, detection of shifts in attention prior to task execution poses a distinct advantage as it allows sufficient time for feedback to be provided to the user to return the attention back to the main task. Maintaining attention to the task is important since attention is an important modulator of plasticity [37, 38]. Contrary to previous studies, in the current work we studied a self-paced BCI. In these conditions, MRCP temporal features alone were less discriminative than a combination of time and frequency features. Nonetheless, the classification accuracy using only temporal features was still 70%, similar to online BCI systems based on ERP or auditory steady-state potentials to classify user attention [11, 39]. ERPs are widely used in BCIs for communication [40, 41]. The performance of these systems is highly dependent on the attention state to the corresponding stimuli. Attention deficits/impairments degrade the performance, particularly in older patients [42, 43]. To date few studies have investigated the effect of providing feedback to the user to allow attention to be redirected to the main task [44]. While this may not be imperative for applications such as spellers, in BCIs designed for neuromodulation attention must be on the task since it influences plasticity [37, 38, 45].

In the current study, we attempted to further enhance classification of attention variations during movement execution by using temporal and spectral features. A combination of temporal and spectral features was superior for discrimination of attention diversion for different types of distractors than either temporal or spectral features alone. Previous studies have relied only on spectral features from EEG signals to reflect changes in attention, alertness and workload [46, 47]. Specifically, for attention to a motor task, classification of attentional state attained values of only 61-68% [48, 49]. Although the latter study is not directly comparable to the current study due to methodological differences, classification accuracies presented here were on average ~84%.

### *B. Channel Location*

The classification performance of attention depended on channel location. For spectro-temporal and temporal features, central and parietal locations were superior for attention discrimination. Central channels over the motor cortical representation of either leg or arm muscles are also optimal for detecting and classifying lower limb or upper limb movements [50-52]. In our previous studies [23, 25], we have shown that the temporal features of MRCPs from the motor cortex were significantly influenced under attention alterations. In this way, the outputs of the central channels may be reliably used for detection of attention variations with the intent to provide appropriate neuro-feedback to the user of the BCI system.

When spectral and spectro-temporal features were used, channels located over the parietal location had a higher accuracy for classification of movement preparation than the other locations for both auditory and visual distractors. This area is known to be involved in providing responses to visual stimuli [53], however auditory information is mainly processed by temporal locations [54]. The possible explanation is that channels located over the parietal cortex can also reflect attention processes since the P300 component was localized in this region [55]. Indeed, it is known that the left parietal locations are involved in discriminating between target and non-target auditory stimuli [56]. The posterior parietal cortex is also an area for sensory-motor integration [57] where sensory input is integrated with motor outputs (sensory-motor transformation). Patients with lesions in this area have no problem in motor movement execution but they are not able to integrate motor functions with sensory information such as using a visual cue to guide movement execution (40). This role of the posterior parietal cortex may explain why channels located here resulted in the higher classification accuracy.

For a self-paced BCI system designed for neuromodulation that uses the MRCP as the control signal [58, 59] we have shown in the past that 9 channels are sufficient for detection of movement intent. Significant plasticity was induced in this associative BCI in healthy participants with very few repetitions and in later studies we demonstrated reasonable a detection accuracy >70% using only a single channel [60]. For clinical applications of this system, it is desirable to minimize the number of channels. However, plasticity induction is modulated by attention [38, 45, 61], and it is known that attention deficits/impairments degrade the level of performance particularly in older patients [42, 43]. In the cue based associative BCI that we have successfully applied in both chronic and acute stroke patients [62, 63], the cue allowed the attention to be focused during the BCI use. In general, such patients respond better when a cue is provided [62]. When the cue is omitted, as in a self-paced BCI, the attention to the task may decrease and this will influence the BCI performance. The results provided here reveal that changes in attention are reliably detected but require at least central and parietal channels. As a next step, detection of these changes will be quantified in real time with the purpose of providing online feedback to the user to maintain high attention state to the main task.

### *C. Limitations*

In the current study, attention to a specific task was diverted by providing both visual and auditory external distractors. In the current study, the effect of internal shifts in attention were not considered although the effect of this has been investigated in previous studies [64, 65]. Since the experiment was conducted in a controlled environment, the experimental conditions did not entail other types of external distractors from the surrounding environment. On the other hand, attention distractors that we are exposed to in real-life conditions can cause shifts of attention either endogenously (voluntary attention) or exogenously (involuntary stimulus-driven attention) [66]. To date it is not possible to quantify endogenous shifts in attention.

The results presented in this work are based on offline analysis. In real-time BCI systems where attention status should be detected and classified online it is likely that the system performance will decrease. This reduction can be compensated by increasing the number of extracted features particularly in the spectral domain. Another method for feature reduction other than PCA may be used for classification enhancement, such as sequential feature selection [67].

## V. Conclusion

The findings presented here demonstrated that it is possible to monitor users' attention diversion under various types of distractors during movement execution, using EEG. This will allow for real-time neurofeedback to be applied as part of a BCI to focus the users' attention on the main task. The results are currently being implemented in the design of a reliable adaptive BCI system where the users' states are continuously monitored. This is particularly beneficial for patients who have difficulties in following the commands of a task due to attention shifts.

## References

[1] P. M. Shende and V. S. Jabade, "Literature review of brain computer interface (BCI) using Electroencephalogram signal," *ICPC,* vol. 2015, pp. 1-5, Apr. 2015.

[2] T. Kim, S. Kim and B. Lee, "Effects of Action Observational Training Plus Brain-Computer Interface-Based Functional Electrical Stimulation on Paretic Arm Motor Recovery in Patient with Stroke: A Randomized Controlled Trial," *Occup. Ther. Int.,* vol. 23(1), pp. 39-47, Mar. 2016.

[3] R. Xu et al., "A Closed-Loop Brain–Computer Interface Triggering an Active Ankle–Foot Orthosis for Inducing Cortical Neural Plasticity," *IEEE Trans. Biomed. Eng.,* vol. 61(7), pp. 2092-2101, 2014-7, 2014.

[4] N. Mrachacz-Kersting et al., "Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity," *J. Physiol.,* vol. 590( 7), pp. 1669-1682, Apr. 2012.

[5] N. Mrachacz-Kersting et al., "Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface," *J. Neurophysiol.,* vol.115(3), pp. 1410-21, Mar. 2015.

[6] F. Galán, F. Oliva and J. Guàrdia, "Using mental tasks transitions detection to improve spontaneous mental activity classification," *Med. Biolog. Eng. Comput.,* vol. 45(6), pp. 603-9, Jun. 2007.

[7] B. A. S. Hasan and J. Q. Gan, "Temporal modeling of EEG during self-paced hand movement and its application in onset detection," *J. Neural Eng.,* vol. 8(5), pp. 056015, Oct. 2011.

[8] N. Wijesuriya et al., "Effects of mental fatigue on 8–13Hz brain activity in people with spinal cord injury," *Conf. Proc. IEEE Eng. Med. Biol. Society,* vol. 2008, pp. 5716-19, Aug. 2008.

[9] R. E. Trachel, M. Clerc and T. G. Brochier, "Decoding covert shifts of attention induced by ambiguous visuospatial cues," *Front. Hum. Neurosci.,* vol. 9, pp. 358, Jun. 2015.

[10] A. Myrden and T. Chau, "Effects of user mental state on EEG-BCI performance," *Front. Hum. Neurosci.,* vol. 9, pp. 308, Jun. 2015.

[11] N. J. Hill and B. Schölkopf, "An online brain–computer interface based on shifting attention to concurrent streams of auditory stimuli," *J. Neural Eng.,* vol. 9(2), pp. 026011, Apr. 2012.

[12] M. De Vos, K. Gandras and S. Debener, "Towards a truly mobile auditory brain–computer interface: Exploring the P300 to take away," *Int. J.Psychophysiol.,* vol. 91(1), pp. 46-53, Jan. 2014.

[13] X. An et al., "Optimizing visual-to-auditory delay for multimodal BCI speller," *Conf. Proc. IEEE Eng. Med. Biol. Society,* vol. 2014, pp. 1226-29, Aug. 2014.

[14] J. Lewald et al., "Perception of stationary and moving sound following unilateral cortectomy," *Neuropsychologia,* vol. 47(4), pp. 962-71, Mar. 2009.

[15] C. F. Altmann et al., "Processing of location and pattern changes of natural sounds in the human auditory cortex," *Neuroimage,* vol. 35(3), pp. 1192-200, Apr. 2007.

[16] L. Battelli, A. Pascual-Leone and P. Cavanagh, "The 'when' pathway of the right parietal lobe," *Trends Cogn. Sci. (Regul. Ed. ),* vol. 11(5), pp. 204-10, May. 2007.

[17] L. Trojano et al., "Matching two imagined clocks: the functional anatomy of spatial analysis in the absence of visual stimulation," *Cereb. Cortex.,* vol. 10(5), pp. 473-81, May. 2000.

[18] M. I. Posner and S. E. Petersen, "The attention system of the human brain," *Annu. Rev. Neurosci.,* vol. 13, pp. 25-42, Jan. 1990.

[19] J. T. Coull, B. J. Sahakian and J. R. Hodges, "The alpha(2) antagonist idazoxan remediates certain attentional and executive dysfunction in patients with dementia of frontal type," *Psychopharmacology (Berl. ),* vol. 123(3), pp. 239-49, Feb. 1996.

[20] M. Corbetta et al., "Voluntary orienting is dissociated from target detection in human posterior parietal cortex," *Nat. Neurosci.,* vol. 3(3), pp. 292-97, Mar. 2000.

[21] M. Corbetta and G. L. Shulman, "Control of goal-directed and stimulus-driven attention in the brain," *Nat. Rev..Neurosci.,* vol. 3(3), pp. 201-15, Mar. 2002.

[22] K. Matsumoto and K. Tanaka, "Conflict and Cognitive Control," *Science,* vol. 303, pp. 969-70, 2004.

[23] S. Aliakbaryhosseinabadi et al., "Influence of attention alternation on movement-related cortical potentials in healthy individuals and stroke patients," *Clin. Neurophysiol.,* vol. 128(1), pp. 165-175, Jan. 2017.

[24] S. Aliakbaryhosseinabadi et al., "Robustness of movement detection techniques from motor execution: Single trial movement related cortical potential," *Conf. Proc. IEEE NER,* vol. 2015, pp. 13-16, 2015.

[25] S. Aliakbaryhosseinabadi et al., "Classification of EEG signals to identify variations in attention during motor task execution," *J. Neurosci. Methods,* vol. 284, pp. 27-34, Jun. 2017.

[26] S. A. Huettel and G. McCarthy, "What is odd in the oddball task?: Prefrontal cortex is activated by dynamic changes in response strategy," *Neuropsychologia,* vol. 42(3), pp. 379-86, 2004.

[27] K. A. Cote, "Probing awareness during sleep with the auditory odd-ball paradigm," *Int. J. Psychophysiol.,* vol. 46(3), pp. 227-41, 2002.

[28] R. Xu et al., "Movement-related cortical potentials in paraplegic patients: abnormal patterns and considerations for BCI-rehabilitation," *Front. Neuroeng.,* vol. 7, pp. 35, Aug. 2014.

[29] E. N. Kamavuako et al., "Comparison of Features for Movement Prediction from Single-Trial Movement-Related Cortical Potentials in Healthy Subjects and Stroke Patients," *Comput. Intell. Neurosci.,* vol. 2015, pp. 1-8, 2015.

[30] M. Jochumsen et al., "Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation," *Med. Biolog. Eng. Comput.,* vol. 54(10), pp. 1491-501, Oct. 2016.

[31] A. J. Nash and M. Fernandez, "P300 and allocation of attention in dual-tasks," *Int. J. Psychophysiol.,* vol. 23(3), pp. 171-80, Oct. 1996.

[32] T. Kida et al., "Resource allocation and somatosensory P300 amplitude during dual task: effects of tracking speed and predictability of tracking direction," *Clinical Neurophysiology,* vol. 115(11), pp. 2616-28, Nov. 2004.

[33] K. S. Baker, T. Piriyapunyaporn and R. Cunnington, "Neural activity in readiness for incidental and explicitly timed actions," *Neuropsychologia,* vol. 50(5), pp. 715-22, Apr. 2012.

[34] D. Baldauf, "Visual Selection of the Future Reach Path in Obstacle Avoidance," *J. Cogn. Neurosci.,* pp. 1-12, Jul. 2018.

[35] A. Bollimunta et al., "Neuronal Mechanisms and Attentional Modulation of Corticothalamic Alpha Oscillations," *J. Neurosci.,* vol. 31(13), pp. 4935-43, Mar. 2011.

[36] M. Doppelmayr, T. Finkenzeller and P. Sauseng, "Frontal midline theta in the pre-shot phase of rifle shooting: Differences between experts and novices," *Neuropsychologia,* vol. 46(5), pp. 1463-67, 2008.

[37] K. Stefan, M. Wycislo and J. Classen, "Modulation of associative human motor cortical plasticity by attention," *J. Neurophysiol.,* vol. 92(1), pp. 66-72, Jul. 2004.

[38] U. Ziemann et al., "Consensus: Motor cortex plasticity protocols," *Brain Stimulation,* vol. 1(3), pp. 164-182, 2008.

[39] D. Kim et al., "Classification of selective attention to auditory stimuli: Toward vision-free brain–computer interfacing," *J. Neurosci. Methods,* vol. 197(1), pp. 180-185, Apr. 2011.
[40] A. Kübler et al., "A Brain-Computer Interface Controlled Auditory Event-Related Potential (P300) Spelling System for Locked-In Patients," *Ann. N. Y. Acad. Sci.,* vol. 1157(1), pp. 90-100, Mar. 2009.
[41] M. S. Treder and B. Blankertz, "(C)overt attention and visual speller design in an ERP-based brain-computer interface," *Behav. Brain Funct.,* vol. 6(1), pp. 28, 2010.
[42] F. Nijboer, N. Birbaumer and A. Kubler, "The Influence of Psychological State and Motivation on Brain-Computer Interface Performance in Patients with Amyotrophic Lateral Sclerosis: a Longitudinal Study," *Front. Neurosci.,* vol. 4, pp. 55, Jul. 2010.
[43] M. Rana et al., "Real-Time fMRI in Neuroscience Research and Its Use in Studying the Aging Brain," *Front. Aging Neurosci.,* vol. 8, pp. 239, Oct. 2016.
[44] T. Sollfrank et al., "The effect of multimodal and enriched feedback on SMR-BCI performance," *Clin. Neurophysiol.,* vol. 127(1), pp. 490-498, Jan. 2016.
[45] P. E. Gander, "Attention and neural plasticity in human auditory cortex," *ProQuest Dissertations and Theses,* 2009.
[46] C. Berka et al., "EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks," *Aviat. Space Environ. Med.,* vol. 78, *(5 Suppl),* pp. B231, May. 2007.
[47] C. Lin et al., "Can arousing feedback rectify lapses in driving? Prediction from EEG power spectra," *J. Neural Eng.,* vol. 10(5), pp. 056024, Oct. 2013.
[48] F. Melinscak, L. Montesano and J. Minguez, "Asynchronous detection of kinesthetic attention during mobilization of lower limbs using EEG measurements," *J. Neural Eng.,* vol. 13(1), pp. 016018, Feb. 2016.
[49] A. Myrden and T. Chau, "A Passive EEG-BCI for Single-Trial Detection of Changes in Mental State," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 25(4), pp. 345-356, Apr. 2017.
[50] E. Kapreli et al., "Lateralization of brain activity during lower limb joints movement. An fMRI study," *Neuroimage,* vol. 32(4), pp. 1709-1709-, Oct. 2006.
[51] M. Wieser et al., "Temporal and spatial patterns of cortical activation during assisted lower limb movement," *Exp. Brain Res.,* vol. 203(1), pp. 181-191, May. 2010.
[52] M. Takemi et al., "Event-related desynchronization reflects downregulation of intracortical inhibition in human primary motor cortex," *J. Neurophysiol.,* vol. 110(5), pp. 1158-66, Sep. 2013.
[53] Y. Li et al., "Brain Electrical Source Analysis of the Response to Visual Target and Distractor Stimuli," vol. 29(5), pp. 933-40, Oct. 2012.
[54] G. F. Potts et al., "High-density recording and topographic analysis of the auditory oddball event-related potential in patients with schizophrenia," *Biol. Psychiatry,* vol. 44(10), pp. 982-89, Nov. 1998.
[55] K. A. Moores et al., "Investigating the generators of the scalp recorded visuo-verbal P300 using cortically constrained source localization," *Hum. Brain Mapp.,* vol. 18(1), pp. 53-77, Jan. 2003.
[56] C. E. Tenke et al., "Hemispatial PCA dissociates temporal from parietal ERP generator patterns: CSD components in healthy adults and depressed patients during a dichotic oddball task," *Int. J. Psychophysiol,* vol. 67(1), pp. 1-16, Jan. 2008.
[57] R. A. Andersen and C. A. Buneo, "Intentional maps in posterior parietal cortex," *Annu. Rev. Neurosci.,* vol. 25, pp. 189, Jan. 2002.
[58] I. K. Niazi et al., "Peripheral Electrical Stimulation Triggered by Self-Paced Detection of Motor Intention Enhances Motor Evoked Potentials," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 20(4), pp. 595-604, 2012.
[59] R. Xu et al., "A Closed-Loop Brain–Computer Interface Triggering an Active Ankle–Foot Orthosis for Inducing Cortical Neural Plasticity," *Biomedical Engineering, IEEE Transactions On,* vol. 61(7), pp. 2092-101, 2014.
[60] M. Jochumsen et al., "Detection of movement intentions through a single channel of electroencephalography," *ICNR*, vol. 2014, pp. 465-72, 2014.
[61] K. Stefan, M. Wycislo and J. Classen, "Modulation of Associative Human Motor Cortical Plasticity by Attention," *J. Neurophysiol.,* vol. 92(1), pp. 66-72, Jul. 2004.
[62] N. Mrachacz Kersting et al., "An associative brain-computer-interface for acute stroke patients," in *Converging Clinical and Engineering Research on Neurorehabilitation II*, N. Mrachacz Kersting, A. J. T. Stevenson, S. Aliakbaryhosseinabadi, A. C. Lundgaard, H. R. Jørgensen, K. Severinsen and D. Farina, Eds. Springer International Publishing, 2017, pp. 841-845, 2017.
[63] N. Mrachacz-Kersting et al., "Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface," *J. Neurophysiol.,* vol. 115(3), pp. 1410-1421, Mar. 2016.
[64] R. T. Tanoue et al., "Differential Frontal Involvement in Shifts of Internal and Perceptual Attention," *Brain Stimul.,* vol. 6(4), pp. 675-682, Jul. 2013.
[65] R. T. Tanoue and M. E. Berryhill, "The mental wormhole: Internal attention shifts without regard for distance," *Atten., Percept. Psychophys.,* vol. 74(6), pp. 1199-1215, Aug. 2012.
[66] M. M. Chun, J. D. Golomb and N. B. Turk-Browne, "A Taxonomy of External and Internal Attention," *Annu. Rev. Psychol.,* vol. 62, pp. 73-101, Jan. 2011.
[67] M. Jochumsen et al., "Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation," *Med. Biol. Eng. Comput.,* pp. 1-11, 2015.